INTELLIGENT ENERGY MANAGEMENT IN SMART BUILDINGS USING MACHINE LEARNING ALGORITHM

A SYNOPSIS

Submitted by

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1. INTRODUCTION

In a contemporary power plant, the load system requires constant current supply. This requires an accurate prediction with minimal inaccuracies on the load demands in the present and the future. In order to accomplish this, researchers and scientists worked to create load forecasting—a highly effective and optional technique that predicts future power consumption—in order to meet this goal. Load forecasting controls a number of decisions, including unit commitment, off-line network, dispatch, fuel allocation, and numerous activities was given by D. W. Bunn [1]. This gives power companies an idea of how much electricity they will consume in the future and how to close the gap between generation capacity and load demand. Demand forecasting lowers electricity generation costs and promotes the growth of a well-organized power utility system. Energy and power utility firms utilize a number of machine learning (ML)-based approaches to forecast energy and power needs and balance generation and demand. A method for controlling supply and demand is load forecasting. Nonetheless, this extremely challenging undertaking necessitates the examination of several influencing direct and indirect elements. While there are several advantages to employing load forecasting techniques, there are certain issues with the systems' accuracy. The process of load forecasting is complex and stochastic. Weather-related elements impact the data when forecasting is completed. Thus, the load for the current hour is determined by the load for the previous hour, the load for the previous day, demographic information, meteorological conditions, the number of devices in the forecasting region, economic information, and the quantity and type of customers discussed by H. S. Hippert, C. E. Pedreira, and R. C. Souza, [2]. In a setting this complex, maintaining a low load forecasting error is crucial. Prediction accuracy is measured using percentages, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The values must be maintained within a range of a few percentage points in order to evaluate a certain algorithm. The load data is a crucial part of the load forecasting model. Understanding the load data consumption pattern is essential for training the model. As a result, the load data needs to be ready for training. The missing numbers and data mistakes are fixed. After then, electrical data is combined with information about other things, like historical events and weather patterns. These kinds of factors affect load forecasting accuracy. After all of the data is analyzed, several models are selected to be used in the load forecasting process. Out of all the models, the most

accurate model is chosen. A number of other factors also affect the model's accuracy. The majority of the elements' fluctuation is mostly dependent on locations and equipment. These should also be taken into account when creating an exact and realistic model. These elements are used as input variables for developing the model. Sometimes, since they are not available, all of these elements are not taken into account. To gather information on the variables needed to create a model in a certain area, reputable sources are consulted. For weather information, these sources may be the weather office, and for time information, the calendar. Electric utility businesses stand to gain greatly from precise and accurate load forecasts, yet needless mistakes can result in significant financial losses and infrastructure loss.

Smart grids, or SGs, have recently drawn a great deal of concern in a number of technological domains, including industry and academics. It is regarded as the astute replacement for outdated electricity systems as discussed by Fadlullah, Z.M, Fouda, [3, 4]. Because it integrates several technologies, such as cloud computing (CC), big data (BD), the internet of things (IoT), etc., it has a huge potential to deliver smart services as given by Habbak, H [5]. SGs are described as a revolutionary digital electric power grid that uses the newest communication technologies to enable bidirectional communication for improved security, efficiency, resilience, and dependability of the electric power systems for increased electrical power generation were discussed by Ibrahem, M.I, Badr and Fouda, M.M., Fadlullah [6, 7]. It is a two-way energy delivery and transportation system that gives consumers the ability to make decisions about their energy use to lower their electricity costs were discussed by Abdulaal, M.J, Ibrahem, M.I and Mahmoud, [8–10]. When it comes to the aftermath of natural disasters and other human attacks, SGs enhance the security measures implemented by Abdalzaher, M.S, Fouda, M.M [11]. On the other hand, it reduces the likelihood that normal grid-related operations would result in harm to people's lives and other physical infrastructure. In terms of setup, SGs modernize the transport section and incorporate electric cars (EVs). Regarding concerns about global warming and the necessity for efficient energy use, SGs reduce energy waste and pollution of the environment from greenhouse gas emissions.

2. LITERATURE REVIEW

AI has produced excellent outcomes in SG applications to improve accuracy, stability, reliability, and efficiency, especially in the LF field. This is especially true of ML and DL models. There is a critical requirement to assess and examine the many ML and DL models in order to determine which is most suited for use with LF approaches in SGs. Within this area, we include multiple survey research that examined LF approaches based on ML and DL. A comparison analysis using the most recent machine learning algorithms that are compatible

with LF approaches of SGs was presented by Bashir, [12]. The decision tree model was found to outperform various machine learning (ML) approaches; some examples of these algorithms are the support vector machine (SVM), K-nearest neighbors method (KNN), neural network (NN), logistic regression, and Naive Bayes. With a perfect precision rate, recall rate of nearly 100%, F1 score of 100%, and accuracy rate of 99.96%, the decision tree performed flawlessly.

Several regression models based LF methods were examined by Yildiz et al. [13]. The conversation revolved over their application, frequently used regression variables, and techniques to improve the efficiency and precision of different algorithms. They examined LF methods for leveraging real applications to forecast the hourly electricity use for the following day. In terms of root mean squared (RMS) and mean absolute percentage error (MAPE) performance, they discovered that the artificial neural network (ANN) with Bayesian regularization back-propagation produced the greatest results. The most appropriate LF technique for a given circumstance or scenario was determined by reviewing the available strategies by Kuster [14]. The following factors were used to compare the different techniques: scale, data sample size, error type, value, inputs, outputs, and time period. The two most often utilized LTLF approaches were regression and multiple regression. ML-based methods, such as artificial neural networks (ANN), support vector machines (SVM), and time series analysis utilizing auto-regressive integrated moving average (ARIMA) and auto-regressive moving average (ARMA), were employed for STLF and VSTLF applications.

Additionally, Deb et al. [15] presented an assessment of the state-of-the-art machine learning methods for time series energy consumption prediction. The nine most popular machine learning-based prediction methods were examined. They talked about hybrid models, which combine two or more prediction methods, and they concluded that the best prediction models for time series energy for the building are hybrid models.

3. OBJECTIVE OF THE RESEARCH WORK

This study work's primary goals are to develop an intelligent Energy Management System (EMS) for a Smart Grid (SG) in order to improve power quality, perform Short Term Load Forecasting in a power system, and estimate energy consumption using machine learning techniques in three phases.

The first phase involves designing the EPO-LSSVM model, an efficient Least Square Support Vector Machines (LS-SVM) for STLF based on Emperor Penguin Optimization (EPO). Three main stages comprise the EPO-LSSVM model's operation: data pre-processing, LS-SVM based prediction, and EPO based parameter adjustment. First, pre-processing of the data is done to eliminate undesirable data and improve the quality of the data. Second, the

electric load is predicted using the LS-SVM model. Furthermore, the LS-SVM model's weight and bias parameters are appropriately adjusted through the application of the EPO algorithm, which draws inspiration from the behavior of emperor penguins. In order to investigate the improved outcomes of the EPO-LSSVM model, a series of simulations were run on the UK Smart Meter dataset, and the results were examined in terms of several measures.

The second phase proposes the use of hybrid shunt filters to improve the microgrid system's power quality. The effectiveness of the shunt hybrid filter is investigated through the use of an improved and complex regulatory technique, called the Adaptive Fuzzy-Neural-Network (AFNN) Controller, in order to achieve a smart grid that functions well under RL supply and load voltage situations. Different management solutions, including Adaptive Fuzzy Sliding (AFS) and Adaptive Fuzzy Back-Stepping (AFBS), are assessed for the proposed regulator. The MATLAB Simulation platform is utilized to do the evaluation.

Three models are used in the third phase to anticipate power consumption: the suggested Prophet Models, non-linear machine learning LSTM (Long Short Term Neural Memory Network), and the traditional state space model ARIMA (Autoregressive Integrated Moving Average). One house close to Paris's real-time smart meter dataset, which spans four years from December 2006 to November 2010, is thought to serve as a test system for the suggested approach. To demonstrate the effectiveness of the suggested Prophet forecasting model, error metrics including Mean Absolute Error (MAE), Root Mean Squared Logarithmic Error (RMSLE), and Root Mean Square error (RMSE), as well as Precision and F1 score, were computed and compared.

4. DESCRIPTION OF THE RESEARCH WORK CARRIED WORK

4.1. Phase 1: Emperor Penguin Optimization based Least Square Support Vector Machines for Short Term Load Forecasting

Three main stages comprise the EPO-LSSVM model's operation: data pre-processing, LS-SVM based prediction, and EPO based parameter adjustment.

4.1.1. LSSVM Model

SVM is the practical application of multidimensional functions to statistical learning techniques. It is a learning system designed for regression goals that has been classified as optical character recognition (OCR). SVM is being used in several engineering fields to provide methods that are more accurate. For simple example input data $x \in R^d$ are regressed by hyperplane f(x):

$$f(x) = \langle w, x \rangle + b \; with \; x \in X, \; b \in R \qquad (1)$$

Where $\langle w, x \rangle$ denotes inner product among x and w. A flat solution can be achieved when w is smaller. Specifically its norm $\|w\|^2 = \langle w, w \rangle$ must be minimal. In the regression example, the loss function and Eq. (2) that allows a small number of mistakes in a particular field epsilon and a small number of slack parameters to deviate from the marginal area by a little amount can be found.

$$\xi = |y_i - f(w, x_i)|$$

$$|\xi|_\varepsilon := \begin{cases} 0 & if\ |\xi| \leq \varepsilon \\ |\xi| - \varepsilon & otherwise \end{cases} \quad (2)$$

Loss function determination provides more adaptability for supporting vector machine regression technique. By assuming positive slack parameters $(\xi_{\mathrm{i}}, \xi_{\mathrm{i}}^*)$ optimization problem is equated as:

$$minimize\ \frac{1}{2}\|\mathrm{w}\|^2 + C\sum_{i=1}^{\ell}(\xi_{\mathrm{i}} + \xi_{\mathrm{i}}^*)$$

$$subject\ to \begin{cases} y_i - \langle \mathrm{w}, x_i \rangle - b \leq \varepsilon + \xi_{\mathrm{i}} \\ \langle \mathrm{w}, x_i \rangle + b - y_i \leq \varepsilon + \xi_{\mathrm{i}}^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \quad (3)$$

Where C represents positive constant and penalizes factor for the information that derives from f are ξ_{i} unit greater than ε.

Traditional SVM has restrictions such as inequality that must be solved using quadratic programming, which increases computing cost for large datasets. In contrast, LSSVM converts all inequality constraints to equality constraint types. As a result, LSSVM solves the linear equation scheme as opposed to quadratic programming. Ultimately, the outcome validates the values and outcomes. In contrast to the support vector in conventional SVM, the support values are pertinent to the error. LSSVM is provided in the regression scenario as:

$$\min \frac{1}{2}\|\mathrm{w}\|^2 + \gamma \frac{1}{2}\sum_{i=1}^{N} \xi_i^2 \quad (4)$$

Where ξ_{i} represents slack parameters and $\gamma \geq 0$ denotes regularization variable. High γ doesn't allow other slack parameters and subsequently increases the method complicity however lower γ implies a method with highly trained error. Thus, it is crucial for finding appropriate value for γ and it is one of LSSVM tuning variables that must be adapted accurately. Assuming subsequent equality constrain in Eq. (5) Lagrangian form of Eq. (4) is determined as Eq. (6)

$$y_i = w\varphi(x_i) + b + \xi_i, i = 1, \ldots, N \quad (5)$$

$$L_{LSSVM} = \frac{1}{2}\|w\|^2 + \gamma \frac{1}{2}\sum_{i=1}^{N} \xi_i^2 - \sum_{i=1}^{N} \alpha_i (w\varphi(x_i) + b + \xi_i - y_i), \quad (6)$$

Where $\alpha_i s(i = 1, \dots, N)$ denotes Lagrange multiplier. By employing optimum condition for Eq. (6) subsequent formulation is given by:

$$\begin{cases} I)\ \frac{\partial L_{LSSVM}}{\partial w} = 0 \rightarrow w = \sum_{i=1}^{N} \alpha_i y_i \varphi(x_i) \\ II)\ \frac{\partial L_{LSSVM}}{\partial b} = 0 \rightarrow \sum_{i=1}^{N} \alpha_i y_i = 0 \\ III)\ \frac{\partial L_{LSSVM}}{\partial \xi_i} = 0 \rightarrow \alpha_i = \gamma \xi_i, i = 1, \dots, N \\ IV)\ \frac{\partial L_{LSSVM}}{\partial \alpha_i} = 0 \rightarrow w\varphi(x_i) + b + \xi_i - y_i = 0,\ i = 1, \dots, N \end{cases} \quad (7)$$

((7)_IV)and (4) reformed optimization problem is given by:

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & k(x_1, x_1) + \frac{1}{c} & \cdots & k(x_1, x_N) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & k(x_N, x_1) & \cdots & k(x_N, x_N) + \frac{1}{c} \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_N \end{bmatrix} \quad (8)$$

Lastly, exclusive form of LSSVM predictive function is given as:

$$f(x) = \sum_{i=1}^{N} \alpha_i\, k(x, x_i) + b. \quad (9)$$

4.1.2. EPO based Parameter Tuning

Since it was discovered in the Antarctic, the emperor penguin's (EP) habit of huddling has an impact on the EPO. The EPs typically migrate in colonies or rafts to forage. It was discovered that this sociable animal's tendency to huddle when foraging is one of its characteristics. Thus, the primary objective of the scientific approach is to identify the effective movers from the swarm. The distance among EP (X_{ep}) are calculated to attain this, after their temperature profile (θ') . The positions of other EPs that are moved in order to achieve the ideal value are used to calculate the effective mover. An outline of this method can be seen in:

The following is an estimate of the EPs' temperature profile:

$$\theta' = \left(\theta - \frac{Iter_{\max}}{C - lter_{\max}}\right) \quad (10)$$

$$\theta = \begin{cases} 0 if R > 0.5 \\ 1 if R < 0.5 \end{cases} \quad (11)$$

The maximum iteration counts, in which C represents present iteration, is stated by $Iter_max$and R denotes arbitrary amount among zero and one.

As EP is generally huddling together to maintain temperatures, preventive measures should be made for protecting themselves from nearby impacts. Because of this, it proposed 2 vectors $(\vec{U})$ and $(\vec{V})$their values are estimated by:

$$\vec{U} = \left\{M \times \left(\theta' + X_{grid}(accuracy)\right) \times Rand\ 0\right\} - \theta \quad (12)$$

$$\vec{V} = Rand(0) \quad (13)$$

$$X_{grid}(accuracy) = \left|\vec{X} - \vec{X}_{\text{ep}}\right| \quad (14)$$

Where M denotes the variable for motion fixed as two, $\vec{x}$ denotes optimal solution, $\vec{x}_{ep}$represents positions of other EPs, [0, 1] and || demotes entire value for *Rand*.

$$\vec{D} = \left|\{S(\vec{U}) \cdot \vec{X}(x) - \vec{V} \cdot \vec{X}_{ep}(x)\}\right| \quad (15)$$

$$S(\vec{U}) = \sqrt{(fe^{-C/v} - e^{-\text{C}})^2} \quad (16)$$

Equations (15) and (16) are created to calculate the distance among EP and optimum fit search agent $(\vec{D}).S()$ displays the social force where the optimum search agent is introduced by Eps, e demonstrating exponential function. The control variables of f and v are the optimum value of f and v in [2, 3] and [1.5, 2] range, correspondingly. Now, based on optimum agent attained by Eq. (17), the EP locations are updated d.

$$\vec{X}_{ep}(x+1) = \vec{X}(x) - \vec{U} \cdot \vec{D}_{ep} \quad (17)$$

It is important to note that the variable range chosen for this study corresponds to the researchers' real research. Thus, as discussed in the previous section, the EPO method is applied to achieve the best possible global value with respect to the operator. The population is started in EPO with randomly generated distinct EP. Figure 1 depicts the EPO flowchart.

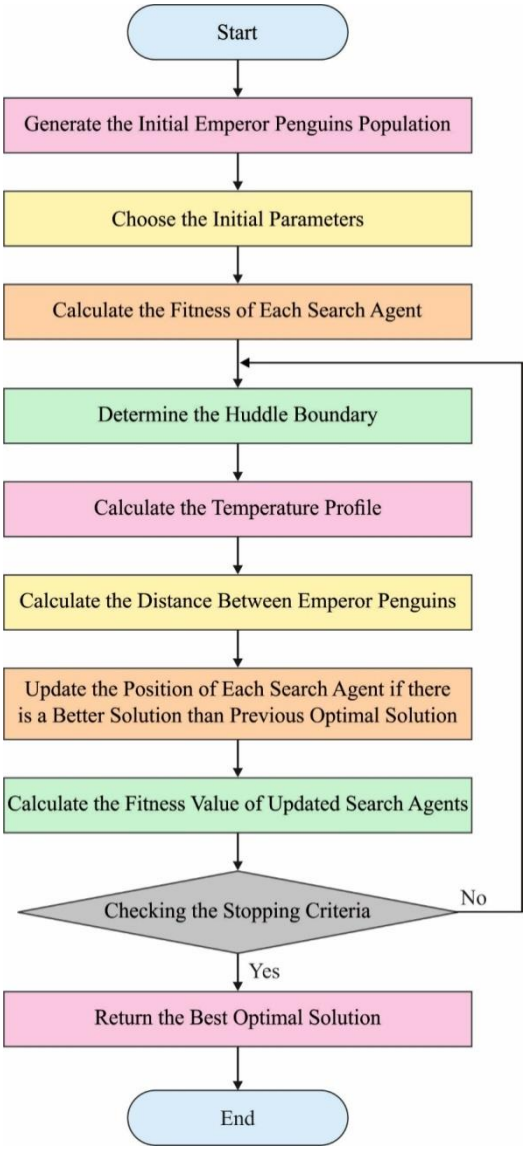
Start
Generate the Initial Emperor Penguins Population
Choose the Initial Parameters
Calculate the Fitness of Each Search Agent
Determine the Huddle Boundary
Calculate the Temperature Profile
Calculate the Distance Between Emperor Penguins
Update the Position of Each Search Agent if there is a Better Solution than Previous Optimal Solution
Calculate the Fitness Value of Updated Search Agents
Checking the Stopping Criteria
No
Yes
Return the Best Optimal Solution
End

Figure 1. Flowchart of EPO

4.2. Design and Development of an Intelligent Energy Management System for a Smart Grid to enhance the Power Quality

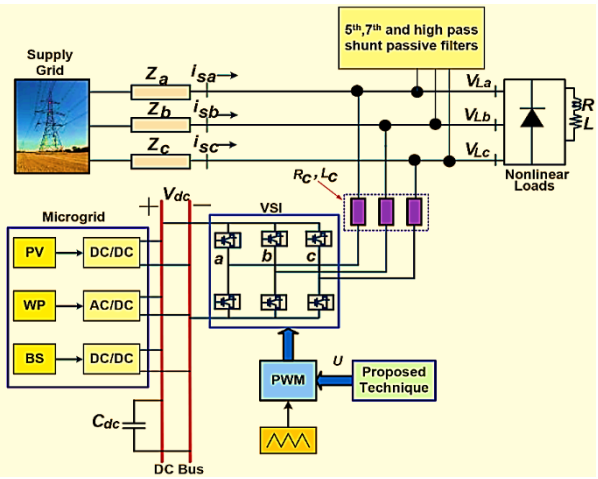

Figure 2. Planned Architecture

The system design of a suggested 3-phase filter element coupled to a microgrid is shown in Figure 2. One clever part of SG is the MG. Because of this, the design of the interface inverters and their clever regulation strategies, which improve the power quality in the smart grid architecture, are the main subjects of this work. An SHF, DC-DC power converters, load fluctuations, and an MG (which consists of a solar, wind, and battery coupled to the SHF's inverter) make up the configuration. The construction of a three-phase SHF is shown in Figure 2. The section on results describes the specifications for every HAF component. V_{s1}, V_{s2} denotes grid voltage, and V_{s3}, whereas i_{s1}, i_{s2}, and i_{s3} denote supply currents. The voltage at the intersection point is denoted by v_1, v_2, and v_3, while i_{L1}, i_{L2}, and i_{L3} denote the load currents. C and v_{dc} remain to denote the capacitance's capacitor and DC bus voltages, respectively. L_c and R_c are the ac side inductor and resistor values.

4.2.1. Various approaches in Control Techniques

The system design of a suggested 3-phase filter element coupled to a microgrid is shown in Figure 2. One clever part of SG is the MG. Because of this, the design of the interface inverters and their clever regulation strategies, which improve the power quality in the smart grid architecture, are the main subjects of this work. An SHF, DC-DC power converters, load fluctuations, and an MG (which consists of a solar, wind, and battery coupled to the SHF's inverter) make up the configuration. The construction of a three-phase SHF is shown in Figure 2. The section on results describes the specifications for every HAF component:

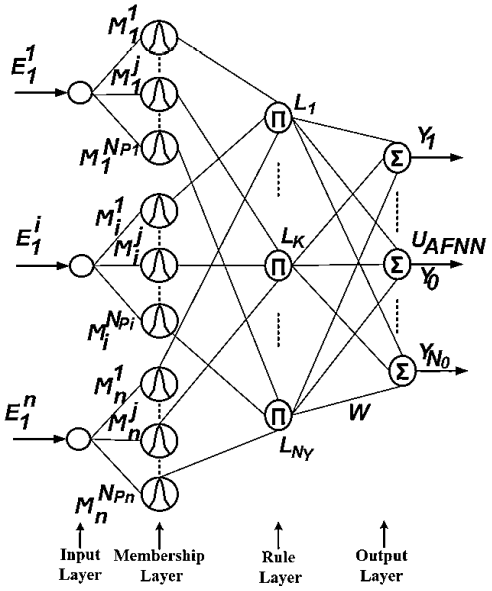

Figure 3. Arrangement of a 4-level Adaptive Fuzzy-Neural-Network

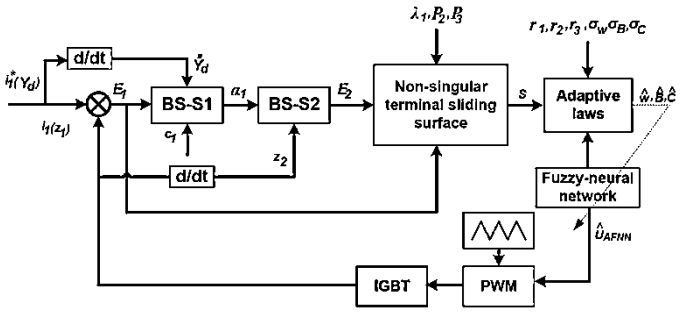

Figure 4. Schematic of Adaptive Fuzzy-Neural-Network

4.3. Real-Time Day Ahead Forecasting for Smart Home using Prophet Method

Prophet was first designed to produce accurate market projections. The following issues, which are typical of many business time series, are attempted to be addressed by this library:

• Human behavior's seasonal influences, including as weekly, monthly, and annual cycles, as well as troughs and peaks on public holidays.

• Outliers;

• Trend shifts brought on by new goods and market developments.

On the additive regression model, the prophet model is built. The prophet model uses changepoints to automatically identify trends in the data. Fourier series is used to simulate the yearly seasonal component; dummy variables are used to represent the weekly components and seasonal vacations.

Three primary mechanisms of a decomposable time series are used by the suggested prophet model: trend, seasonality, and holidays.

$$y\,(t) = \; g(t) + \; s(t) + h(t) + \varepsilon(t) \qquad (18)$$

y(t) : Predicted term at time t

g(t): Linear or logistic growth curve piece by piece to model non-periodic time series changes

s(t): Periodic variation(e.g. weekly/yearly seasonality)

h(t): Holidays effect (user provided) with uneven plan

εt: Error term refers to any uncommon changes that the model does not accommodate

Non-periodic changes in the value of the time series is modelled by trend function g(t). Periodic changes (e.g., weekly and yearly seasonality) of the time series are modelled by s (t).Effects of holidays that occur over one or more days on potentially irregular schedules are modelled by h (t). The error term εt reflects any idiosyncratic changes that the model does not accommodate; εt is normally distributed.

Prophet does not examine the time-based dependence of individual observations in a time series; instead, it presents the prediction problem as a curve-fitting exercise. In order to

give a dynamic framework for the seasonality impacts and forecasts, Prophet focuses on the Fourier series. The following function approximates the s(t) seasonal effects by the following Fourier series:

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right) \tag{18}$$

P is the period (365.25 for yearly data and 7 for weekly data).

5. SIMULATION RESULT

5.1. Phase 1: Emperor Penguin Optimization based Least Square Support Vector Machines for Short Term Load Forecasting

Numerous attributes are included in the dataset, including Acorn group, Date and Time, Plan used, Meter reading (Kwh), and Household ID. The UK Smart Meter dataset is used to validate the proposed EPO-LSSVM model, and Table 1 presents an accuracy analysis of the results. The accuracy analysis of the suggested EPO-LSSVM model using training, validation, and testing data is shown in Figure 5. With an accuracy of 30.88%, the RF model has the lowest predictive efficiency when compared to the EPO-LSSVM model's performance on the training dataset. Subsequently, the KNN and RPART models have achieved somewhat improved predictive results, with 36.15% and 36.36% accuracy, respectively. Concurrently, the NNET model has shown a 39.99% accuracy rate and a modest outcome. The suggested EPO-LSSVM model has guaranteed improved performance with an accuracy of 87.46%, even if the SVR model has demonstrated nearly ideal results with an accuracy of 43.98%. With an accuracy of 33.28%, the KNN model has the lowest predictive efficiency when compared to the EPO-LSSVM model's performance on the validation dataset. Subsequently, the RF and RPART models achieved somewhat improved prediction results, with accuracy rates of 37% and 37.89%, respectively. Concurrently, the NNET model has shown a decent result with 41.60% accuracy. While the SVR model has demonstrated nearly ideal results (44.43% accuracy), the suggested EPO-LSSVM model has guaranteed improved performance (89.53% accuracy).

Table 1. Result Analysis of Existing with Proposed EPO-LSSVM Method on Applied Dataset

Methods	Accuracy (%)		
	Training	Validation	Testing
EPO-LSSVM	87.46	89.63	90.31
KNN	36.15	33.28	41.37
RPART	36.36	37.00	35.12
RF	30.88	37.89	41.07
NNET	39.99	41.60	42.26
SVR	43.98	44.43	47.02

With an accuracy of 35.12%, the RPART model has the lowest predictive efficiency after examining the EPO-LSSVM model's performance on the testing dataset. The RF and KNN models, which have accuracy rates of 41.07% and 41.37%, respectively, have thus produced somewhat improved predicted results. Concurrently, the NNET model has shown 42.26% accuracy and modest results. The suggested EPO-LSSVM model has guaranteed improved performance with an accuracy of 90.31%, even if the SVR model has demonstrated nearly ideal results with an accuracy of 47.02%.

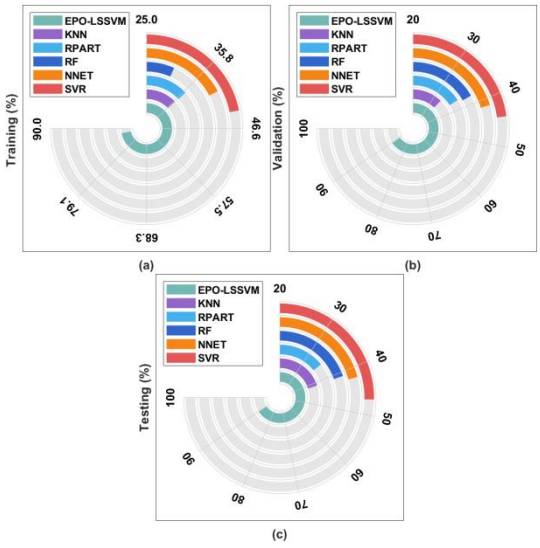

Figure 5. Accuracy analysis of EPO-LSSVM model with existing techniques

5.2. Design and Development of an Intelligent Energy Management System for a Smart Grid to enhance the Power Quality

When evaluating SHF's performance in a grid-connected system, MATLAB/Simulink software is frequently utilized. Table 2 displays the control variable for the suggested system. The SHF is employed in a range of operational scenarios. By integrating current harmonic mitigation

with effective reactive power support, the shunt hybrid filter improves power quality. In particular, non-loads continue to be connected to the power grid at a shared point to demonstrate the techniques' robustness. The report outlines a harmonics analysis in several loads to determine whether AFS, AFBS, and ANFNN controller is best.

Table 2. Analyzed parameters at steady state

S.No	Load Condition	Controller technique	P in kW	Q in VAR	Cos Ø	THD %
1	RL load	AFNN	7.262	-5.52	0.9987	2.240
		AFBS	7.299	5.32	0.9877	3.410
		AFS	7.275	-0.2924	0.9928	1.830
		Without SHF	7.311	425.01	0.9728	32.77

Table 3. Under unbalanced loading conditions, load current, source current and RMS value at individual phase and distortion value

Parameters	Phases	Different techniques without SHF	AFS	AFBS	AFNN
Load Current THD %	A	15.54	15.24	15.58	15.52
	B	18.69	18.15	18.71	18.59
	C	13.48	13.18	13.58	13.24
Input Current THD %	A	13.44	2.15	1.88	1.85
	B	17.91	2.38	2.15	1.82
	C	12.98	2.28	2.08	1.80
RMS Value of Load Current	A	19.98	18.88	19.28	19.01
	B	15.99	15.95	15.82	15.85
	C	23.90	22.12	22.20	22.17
RMS Value of input Current	A	19.98	17.52	17.50	17.41
	B	17.99	17.20	17.22	17.65
	C	24.99	16.99	16.96	16.88

5.3. Real-Time Day Ahead Forecasting for Smart Home using Prophet Method

The mean value of the projected and actual values for the ARIMA, LSTM, and Prophet models based on daily, weekly, monthly, and quarterly intervals is shown in Table 4.

Table 4. Forecasting performance

Seasonal	Global Active power in kilo watts						
	Actual	ARIMA		LSTM		Prophet	
		Forecast	Error	Forecast	Error	Forecast	Error
Daily	0.9859	1.2553	0.2694	1.0883	0.1024	0.9909	0.005
Weekly	0.9928	1.2542	0.2614	1.0914	0.0986	1.0005	0.0077
Monthly	0.965	1.2182	0.2532	1.0784	0.1134	0.9764	0.0114
Quarterly	0.9819	1.236	0.2541	1.0838	0.1019	0.9941	0.0122
Yearly	0.9859	1.2553	0.2694	1.0883	0.1024	0.9909	0.005

The ARIMA model's seasonal parameters, P, D, Q, and s, were adjusted to their ideal values during the course of 1452.39 seconds of tuning. The LSTM model can recognize the seasonal influence because its gates determine which sequence data should be retained or discarded. With the help of the trained seasonal effect, LSTM can forecast outcomes by sending pertinent data down a lengthy chain of sequences. Table 4 demonstrates that the predicted error is better than ARIMA. The suggested Prophet model, which can track trends and seasonality, has less projected error when compared to ARIMA and LSTM. Unlike ARIMA models, prophet models do not require tuning over time.

Figure 6 displays the global active power consumption in real time for the year 2010 together with the anticipated power consumption of LSTM, ARIMA, and the suggested Prophet Model. It demonstrates how much more closely the Prophet Model prediction matches the actual power consumption.

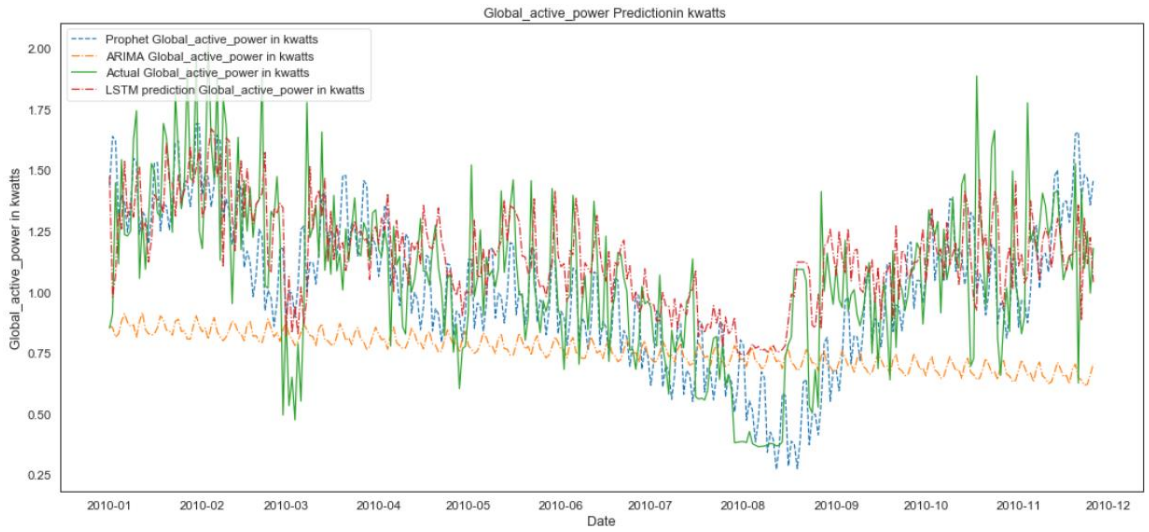

Figure 6. ARIMA, LSTM, Prophet with Global Active Power in kW

7. CONCLUSION

Three phases of investigation have been conducted in this study on the use of machine learning techniques for load forecasting and power quality enhancement in power systems.

The EPO-LSSVM model, an EPO-based LS-SVM model for STLF, is proposed in the first phase. Data pre-processing is done in the first stage to eliminate extraneous data and improve the quality of the data. Next, the electric load is predicted using the LS-SVM model. Furthermore, the LS-SVM model's weight and bias parameters are properly adjusted through the application of the EPO algorithm, which draws inspiration from the actions of emperor penguins. In order to investigate the improved outcomes of the EPO-LSSVM model, a series of simulations were run on the UK Smart Meter dataset, and the results were examined in terms of several measures. The final findings demonstrated how the EPO-LSSVM model outperformed the other approaches under comparison in terms of prediction accuracy.

SHF is employed in this research's second phase along with improved smart regulation strategies. AFNN with NTSMC improves efficiency for RL load. The recommended method is connected to an additional controller that has AFBS, AFS, and RL load. The proposed system operates well under both imbalanced non-linear loading changes and steady-state, dynamic loading conditions. The results of the simulations conducted under different operating conditions demonstrate that the proposed method performs more efficiently and demonstrates good stability, dynamic performance, and robustness under a wide range of conditions. A fast and limited solution is provided by AFNN. The recommended filter reduces the amount of THD and compensates for harmonic perturbations more quickly than the other two standard controllers. An additional evaluation of the proposed controller is carried out in an MG scenario with different wind and solar irradiation. Furthermore, various approaches are required in subsequent work to support the transition to the power grid; for instance, tactics for determining pertinent indicators and constraints for PQ issues ranging from prolonged outages and slow grid voltage fluctuations to interharmonics and transients. comprehensive examinations of any potential sources of voltage and current fluctuations that could affect the network as a result of new devices being added to the network.

The Prophet Model was suggested and put into practice in the third phase, and the results were compared with those of ARIMA and LSTM. Based on basic train test split validations conducted over varying time horizons, the suggested Prophet Forecast model outperforms LSTM and ARIMA in terms of prediction errors. The results demonstrate that the suggested Prophet Forecast model performs better than every other model. The error measures show that it produces the lowest RMLSE, MSE, RMSE, and MAE. In addition, the suggested

Prophet model outperforms the LSTM and ARIMA models in terms of F1 score and precision. Compared to ARIMA and LSTM models, the suggested model requires less training time. The comparison's findings demonstrate that the Prophet Prediction model identifies the most effective substitute techniques that have been thoroughly evaluated. This type of online short-term forecasting is crucial in the smart grid context. A consumer can use the Prophet model to forecast how much electricity they will use tomorrow and plan their energy management accordingly.

8. ORGANIZATION OF THE THESIS

The following is the thesis's framework:

Information on load forecasting in power systems and smart grids is given in **Chapter 1**. This chapter also demonstrates the many load forecasting approaches that are accessible, the thesis's goals, and the algorithms and strategies that are suggested to accomplish those goals.

A portion of the research on load forecasting in power systems and smart grids is reviewed in **Chapter 2**. The benefits and drawbacks of the current approach are also covered. The research gap in load forecasting for power systems and smart grids is also covered in this chapter.

In **Chapter 3**, the data and methods for modelling a Real-Time Day Ahead forecasting for Smart Homes using the prophet method, designing an Intelligent Energy Management System for a Smart Grid to improve the power quality, and using Emperor Penguin Optimization based Least Square Support Vector Machines for Short Term Load Forecasting are covered.

In **Chapter 4**, the outcomes and their implications are discussed for the Least Square Support Vector Machines with Emperor Penguin Optimization based Short Term Load Forecasting, the Intelligent Energy Management System designed for a Smart Grid to improve the quality of the power, and the Prophet method used to model a Real-Time Day Ahead forecasting for Smart Homes.

The study findings and noteworthy contributions are compiled in **Chapter 5**. It also wraps up the thesis and suggests some areas for further investigation.

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LIST OF PUBLICATIONS

1. V. Nisha, V.Vasudevan, A.Ramkumar and A. Sheela, Real-time day ahead energy management for smart home using machine learning algorithm, *Journal of Intelligent & Fuzzy Systems*, **41** (2021) 5665–5676.
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